JOURNAL OF TRAFFIC AND TRANSPORTATION ENGINEERING (ENGLISH EDITION) 2016; 3 (3): 226–235

Available online at www.sciencedirect.com
ScienceDirect
journal homepage: www.elsevier.com/locate/jtte

Original Research Paper

Incorporating vehicle mix in stimulus-response car-following models

Saidi Siuhi [a,*], *Mohamed Kaseko* [b]

[a] *Department of Civil Engineering, Abu Dhabi University, Abu Dhabi, United Arab Emirates*
[b] *Department of Civil and Environmental Engineering, University of Nevada, Las Vegas, NV 89154, USA*

ARTICLE INFO

Article history:
Available online 14 May 2016

Keywords:
Car-following
Stimulus-response
Acceleration/deceleration
Vehicle mix
Driver response time lag

ABSTRACT

The objective of this paper is to incorporate vehicle mix in stimulus-response car-following models. Separate models were estimated for acceleration and deceleration responses to account for vehicle mix via both movement state and vehicle type. For each model, three sub-models were developed for different pairs of following vehicles including "automobile following automobile," "automobile following truck," and "truck following automobile." The estimated model parameters were then validated against other data from a similar region and roadway. The results indicated that drivers' behaviors were significantly different among the different pairs of following vehicles. Also the magnitude of the estimated parameters depends on the type of vehicle being driven and/or followed. These results demonstrated the need to use separate models depending on movement state and vehicle type. The differences in parameter estimates confirmed in this paper highlight traffic safety and operational issues of mixed traffic operation on a single lane. The findings of this paper can assist transportation professionals to improve traffic simulation models used to evaluate the impact of different strategies on ameliorate safety and performance of highways. In addition, driver response time lag estimates can be used in roadway design to calculate important design parameters such as stopping sight distance on horizontal and vertical curves for both automobiles and trucks.

1. Introduction

A car-following model is a mathematical expressions that emulate drivers' behavior following another vehicle in a single lane. Studies on the car-following model started in the early 1950s (Pipes, 1953; Reuschel, 1950). Reuschel and Pipes were independently inspired by the vehicle separation law of the California Vehicle Code, which states that "A good rule for following another vehicle at a safe distance is to allow yourself the length of a car (about fifteen feet) for every ten miles per hour you are traveling." They developed safe distance model as a linear function of speed assuming that drivers reacted instantaneously to the actions of a leading vehicle. Forbes

* *Corresponding author*. Tel.: +971 2 501 5216; fax: +971 2 586 0182.
E-mail addresses: saidi.siuhi@adu.ac.ae (S. Siuhi), mohamed.kaseko@unlv.edu (M. Kaseko).
Peer review under responsibility of Periodical Offices of Chang'an University.
http://dx.doi.org/10.1016/j.jtte.2016.05.002

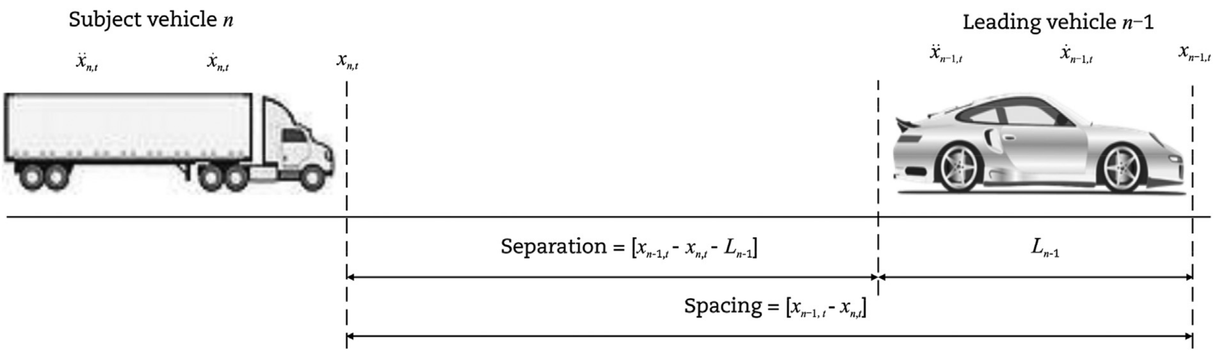

Fig. 1 – Definitions and notations.

(1963) modified the model by incorporating a driver reaction time.

In 1958, researchers associated with the general motors (GM) developed a series of five stimulus-response car-following models. The concept of the GM models was similar to those of Reuschel, Pipes, and Forbes but assumed that driver response was a function of a stimulus and driver sensitivity. Stimulus was defined as the relative speed between the two following vehicles and driver sensitivity was assumed to be a function of vehicle speed and spacing. Gazis et al. (1961) generalized the models by further improving the driver sensitivity term. This resulted in a nonlinear model that had the driver sensitivity term proportional to the speed of the following vehicle and inversely proportional to vehicle spacing.

Ozaki (1993) and Subramanian (1996) modified the GM model by separating acceleration and deceleration responses. Subramanian determined that drivers reacted faster under acceleration response than deceleration response which is counter intuitive. Deceleration is a response related to safety, therefore, one would expect a faster response time. Ahmed (1999) improved Subramanian's model by adding traffic density in the sensitivity term and assumed nonlinearity in the stimulus term. Similarly, Toledo (2003) re-estimated parameters of Subramanian's model. For acceleration response, results of both Ahmed and Toledo showed that acceleration increased with speed and decreased with vehicle spacing, which was unexpected. For the deceleration model, they both removed speed from the models as it was statistically insignificant. Having a deceleration model that does not incorporate speed is unrealistic.

To address limitations of the generalized GM model reviewed above, numerous studies have attempted to improve the structure to reasonably replicate car-following behavior (Alvarez et al., 2003; Bonsall et al., 2009; Brackstone et al., 2009; Mehmood and Easa, 2010; Newell, 2002; Siuhi and Kaseko, 2013; Wang et al., 2004; Winsum and Brouwer, 1997; Xin et al., 2008). Other studies have attempted to improve car-following particularly in modeling driving behavior, traffic safety, and psychology (Dowling et al., 2004; Wang et al., 2010a,b). Most recent studies have devoted effort and emphasis to understand drivers' decision making while following another vehicle in the same lane (Wang et al., 2011; Winsum and Brouwer, 1997).

Drivers' decision making of the subject vehicle following the leader vehicle depends on many factors including vehicle separation, differential speed, and characteristics of traffic stream (Ranney, 1994; Winsum and Heino, 1996). Due to many reasons, sometimes drivers make unconscious and/or unexpected responses which are not responses related to the actions of the leading vehicle (Siuhi, 2009; Siuhi and Kaseko, 2013). As a result, emulating driving behavior on drivers' awareness under different driving conditions still motivates researchers (Bonsall et al., 2009; Sukthankar, 1997; Wang et al., 2010a,b).

In summary, existing GM-like stimulus-response car-following models still have one major shortcoming; they fail to account for vehicle mix. The models assume that drivers have similar driving behavior regardless of the type of vehicle being driven and/or followed, which is unrealistic. In reality, drivers behave differently depending on type of vehicle being followed and/or driven. For example, large trucks generally block the ability of drivers of automobiles to see beyond them due to their large dimensions. Thus, drivers of automobiles traveling behind trucks may behave more differently than when traveling behind other automobiles. Likewise, trucks have low acceleration/deceleration capabilities than automobiles and try to compensate these limitations by keeping longer vehicle separation than automobiles.

To address this shortcoming of the GM-like stimulus-response car-following models, the objectives of this paper were:

1. To develop and estimate a set of stimulus-response car-following models that incorporate vehicle mix such as automobiles and trucks. Models estimated were for acceleration and deceleration responses for different types of vehicles being driven and/or followed,
2. To evaluate whether estimated model parameters were different for different types of vehicles being driven and/or followed, and
3. To evaluate spatial transferability of the estimated model parameters.

2. Generalized stimulus-response car-following model

This paper uses the following definitions and notations in describing the car-following models. Consider two following vehicles traveling from left to right as shown schematically in

Fig. 1. Vehicle $n-1$ is a leading vehicle with length L_{n-1} and vehicle n is a subject vehicle. The subscript t denotes the time of observation of vehicle position, velocity, and acceleration/deceleration.

In Fig. 1, $x_{n-1,t}$ is the position of a leading vehicle $n-1$ at time t, $x_{n,t}$ is the position of a subject vehicle n at time t, $\dot{x}_{n-1,t}$ is the speed of the leading vehicle $n-1$ at time t, $\dot{x}_{n,t}$ is the speed of the subject vehicle n at time t, $\ddot{x}_{n,t}$ is the acceleration/deceleration of a subject vehicle n at time t, $\ddot{x}_{n-1,t}$ is the acceleration/deceleration of a leading vehicle $n-1$ at time t, $[x_{n-1,t}-x_{n,t}]$ is the spacing between the two vehicles at time t, $[x_{n-1,t}-x_{n,t}-L_{n-1}]$ is the separation between two following vehicles at time t, L_{n-1} is the length of the leading vehicle $n-1$.

The generalized form of the GM-like stimulus-response car-following models (Gazis et al., 1961) is shown in Eq. (1).

$$\ddot{x}_{n,t}=\beta_0[\dot{x}_{n,t-\Delta t}]^{\beta_1}[x_{n-1,t-\Delta t}-x_{n,t-\Delta t}-L_{n-1}]^{\beta_2}[\dot{x}_{n-1,t-\Delta t}-\dot{x}_{n,t-\Delta t}]^{\beta_3} \tag{1}$$

where Δt is the driver response time lag, $\dot{x}_{n,t-\Delta t}$ is the speed of a subject vehicle n at time $t-\Delta t$, $\dot{x}_{n-1,t-\Delta t}$ is the speed of a leading vehicle $n-1$ at time $t-\Delta t$, $[\dot{x}_{n-1,t-\Delta t}-\dot{x}_{n,t-\Delta t}]$ is the relative speed between the two vehicles at time $t-\Delta t$, $x_{n-1,t-\Delta t}$ is the position of the leading vehicle $n-1$ at time $t-\Delta t$, $x_{n,t-\Delta t}$ is the position of the subject vehicle n at time $t-\Delta t$, $[x_{n-1,t-\Delta t}-x_{n,t-\Delta t}-L_{n-1}]$ is the vehicle separation at time $t-\Delta t$, β_0 is the driver sensitivity constant, β_1 is the speed parameter, β_2 is the relative speed parameter, β_3 is the vehicle separation parameter.

The parameters of the model are estimated for acceleration and deceleration response based on Eq. (2) (Siuhi and Kaseko, 2013).

$$\text{Response}_{n,t}=\begin{cases}\text{acceleration} & [\dot{x}_{n-1,t-\Delta t_1}-\dot{x}_{n,t-\Delta t_1}]\geq z_1\\ \text{deceleration} & [\dot{x}_{n-1,t-\Delta t_2}-\dot{x}_{n,t-\Delta t_2}]\leq z_2\\ \text{no}-\text{response} & \text{otherwise}\end{cases} \tag{2}$$

where Δt_1 is the driver response time lag for acceleration, Δt_2 is the driver response time lag for deceleration, z_1 is the stimulus threshold for acceleration, $z_1>0$, z_2 is the stimulus threshold for deceleration, $z_2<0$.

The models estimated in this paper are the extension of the model developed by Siuhi and Kaseko (2013) but have three significant contributions as follows:

- Incorporates vehicle and driver heterogeneity in the acceleration and deceleration models by estimating different sub-models by type of vehicle being followed and/or driven. Sub-models were estimated for "automobile following automobile," "automobile following truck," and "truck following automobile".
- Estimates parameters for acceleration and deceleration responses separately, obtain distribution of parameters, and aggregate results across different pairs of vehicle following types, and
- Evaluates spatial transferability of the parameters to highways with similar geometric and traffic characteristics in the same region.

The parameters β_j in Eq. (1) are expected vary for different drivers due to the differences in aggressiveness and capabilities of individual driver. The variation is also attributed to the difficulty of drivers to precisely estimate differential speed and distance with the leading vehicle. Furthermore, magnitude of the parameters is expected to be different for different vehicle types (automobiles versus trucks).

Driver response time lags for both acceleration and deceleration responses were assumed to be different based on asymmetric microscopic driving behavior reported in past studies (Edie, 1965; Foote, 1965; Forbes, 1963; Yeo, 2008; Yeo and Skabardonis, 2009). The thresholds were also assumed to be different for different drivers, and also for the same driver, the magnitudes of z_1 and z_2 can be different. This assumption is based on the findings of Todosiev (1963) who found that positive response threshold is greater than the negative response threshold for a given vehicle separation. Similarly, Michaels (1965) also found that the distance for detecting a slower leading vehicle is smaller compared to the one for detecting a faster leading vehicle. These findings suggest that drivers are more sensitive under deceleration response than acceleration response. Thresholds, however, are likely to be a function of speed and vehicle separation. At slower speeds and smaller vehicle separations, threshold may be smaller than the thresholds at higher speeds and larger vehicle separations. This paper simplified the models by determining one value of threshold that is independent of these factors but the value is different for acceleration and deceleration responses.

For acceleration response, the larger positive relative speed, the larger the magnitude of the expected acceleration value for a following vehicle. Hence, the sign of the relative speed parameter β_3 is expected to be positive. It is also hypothesized that drivers are less aggressive when accelerating from a higher speed than from a lower speed, and also vehicle acceleration capabilities are lower at higher speeds. Therefore, the magnitude of the acceleration response is expected to be lower at higher speeds. This suggests that the expected sign for speed parameter β_1 is negative. Equally, the magnitude of the acceleration value is expected to be higher for bigger vehicle separation than for smaller separation between following vehicles. Hence, the sign of the vehicle separation parameter β_2 for acceleration response is expected to be positive.

For deceleration response, it is expected that the larger the negative relative speed, the larger the magnitude of the deceleration response for a following vehicle. Hence, the sign of the relative speed parameter β_3 is expected to be positive. It is also hypothesized that for safety reasons, drivers will respond with higher deceleration rates at higher speeds than at lower speeds. This suggests that the expected sign for the speed parameter β_1 is positive. For similar reasons, when the vehicle separation is smaller, the magnitude of deceleration response is expected to be higher. Therefore, the expected sign of vehicle separation parameter β_2 is negative.

Table 1 presents a summary of the expected signs of the parameters for acceleration and deceleration responses shown in Eq. (1).

2.1. *Parameters estimation approach*

This study estimated the parameters of the models in two stages. The first stage estimated the disaggregate parameters for each individual subject vehicles. The second stage estimated the aggregate parameters for all vehicles selected in this research. The equations of the proposed models in this research were nonlinear in parameters. The disaggregate parameters of the models for each individual vehicles were estimated using nonlinear least squares regression. The models proposed can be rewritten in general form as

$$f(x_{n,t}) = f(\beta, X_{n,t-\Delta t}) + u_{t-\Delta t} \quad t = 1, 2, \cdots, p \tag{3}$$

where $f(x_{n,t})$ is the acceleration/deceleration of the subject vehicle at time t, β is the k-vector of unknown parameters, $X_{n,t-\Delta t}$ is the vector of explanatory variables of the subject vehicle at time $t-\Delta t$, $u_{t-\Delta t}$ is the error term at time $t-\Delta t$, p is the number of observations.

The error term accounts for the unobserved factors and for estimation purpose it is assumed to be normally identically distributed random variable with mean zero and constant variance i.e. $u_{t-\Delta t} \sim \mathrm{NID}(0, \sigma^2), E(u_{t-\Delta t}) = 0$, and $\mathrm{Var}(u_{t-\Delta t}) = \sigma^2$.

In a nonlinear model the unknown parameters of the models are estimated by maximizing log likelihood function. The log likelihood function for the nonlinear regression equation is defined as

$$\ell(\beta, \sigma^2) = \frac{1}{(2\pi\sigma^2)^{n/2}} \mathrm{e}^{\left\{-\frac{\sum_{t=1}^{p}\left[f(x_{n,t}) - f(\beta, X_{n,t-\Delta t})\right]^2}{2\sigma^2}\right\}} \tag{4}$$

The log likelihood is maximized when the sum of squared residuals, $S(\beta)$ is minimized.

$$S(\beta) = \sum_{t=1}^{p} \left[f(x_{n,t}) - f(\beta, X_{n,t-\Delta t})\right]^2 \tag{5}$$

Differentiating the objective function, $S(\beta)$ with respect to β and equating it to zero yields:

$$\frac{\partial S(\beta)}{\partial \beta} = -2\sum_{t=1}^{p}\left[f(x_{n,t}) - f(\beta, X_{n,t-\Delta t})\right]\frac{\partial f(\beta, X_{n,t-\Delta t})}{\partial \beta} = 0 \tag{6}$$

Setting the partial derivatives to zero produces equations for estimating the parameters of the regression equation. The equations formed do not have closed form solution, thus, they require solution by the numerical optimization method. This study used the Stata program to estimate parameters of the models. The Stata implements a modified Gauss-Newton method in estimating parameters of the models (Baum, 2006). The parameters were estimated using nonlinear least squares command nl implemented in the Stata program.

Table 1 – Expected parameter signs.

Parameter	Acceleration response	Deceleration response
Speed parameter β_1	Negative	Positive
Separation parameter β_2	Positive	Negative
Relative speed parameter β_3	Positive	Positive

This paper used vehicle trajectory data collected by the Federal Highway Administration (FHWA) as part of the next generation simulation (NGSIM) study (NGSIM, 2008) to calibrate the models. The data contains 45 min of detailed vehicle trajectory data collected on a 2100-feet southbound section of Interstate 101 in Los Angeles, California, on a weekday from 7:50–8:35 a.m. The section has five through lanes and one auxiliary lane. The auxiliary lane is approximately 698 feet long. The data was collected using eight synchronized digital video cameras installed on an adjacent 36-storey building. A full detailed description of technology and methodology used to collect and process the data are available at the NGSIM website at http://ngsim.fhwa.dot.gov/.

To minimize the random fluctuations of the instantaneous trajectory data, this data was further filtered by taking the moving averages for each of the variables over 0.5 s. The problem of using unfiltered data was also observed and reported by Treiber and Kesting (2008). The following criteria were used to select vehicles for this study:

- Only pairs of vehicles that were following each other over the entire section without changing lanes and without being interrupted by another vehicle were selected. The rationale for excluding vehicles that change lanes was based on the assumption that drivers when changing lanes may exhibit different characteristics from those of simple car-following behavior.
- Only vehicles that traveled in the middle three through lanes were selected in order to avoid the impact of weaving movements on the auxiliary and the right-most lanes as well as the left-most lane, which is a high-occupancy vehicle (HOV) lane.

Table 2 summarizes simple descriptive statistics of variables used to estimate model parameters for different pairs of following vehicles. In most car-following scenarios shown in the table, these statistics show the expected magnitude. For example trucks following automobiles have higher mean vehicle separation values than automobiles following automobiles and automobiles following trucks. However, the mean acceleration values are higher than the deceleration value, which is unexpected.

This paper assumed that the parameters β_j varied for different drivers. The variations were attributed to random aggressiveness and capabilities of individual drivers responding to various car-following situations. Vehicle trajectory data for each individual vehicle was used to calibrate the acceleration and deceleration sub-models for the vehicle. This resulted in as many different β_j parameters as the number of vehicle pairs selected. Individual parameter values for the group of vehicles in each sub-model category were aggregated to obtain mean parameter values and standard deviations that were representative of all the vehicles.

It is clear that the parameters are interrelated and cannot be estimated independently. It is worthwhile mentioning that measurement taken over time, such as vehicle trajectory, is generally serially correlated. This violates the homoskedasticity assumption of the error term. The error term in such trajectory data will exhibit heteroskedasticity which

Table 2 – Variable descriptive statistics.

Variable	Mean	Std	Minimum	Maximum
Automobile following automobile ($n = 75$)				
Acceleration (m/s^2)	0.62	0.55	0.02	3.36
Deceleration (m/s^2)	0.58	0.55	0.02	3.35
Positive relative speed (kph)	3.14	2.80	0.00	23.26
Negative relative speed (kph)	2.98	2.67	0.00	28.82
Speed (kph)	26.39	13.10	0.00	74.30
Vehicle separation (m)	14.22	7.44	0.24	72.25
Automobile following truck ($n = 25$)				
Acceleration (m/s^2)	0.62	0.54	0.02	2.93
Deceleration (m/s^2)	0.42	0.44	0.02	2.74
Positive relative speed (kph)	3.15	2.69	0.00	3.38
Negative relative speed (kph)	2.86	2.66	0.00	26.22
Speed (kph)	32.32	13.79	0.00	71.47
Vehicle separation (m)	15.17	8.48	0.58	45.84
Truck following automobile ($n = 32$)				
Acceleration (m/s^2)	0.61	0.536	0.02	2.76
Deceleration (m/s^2)	0.48	0.510	0.02	2.85
Positive relative speed (kph)	6.10	6.23	0.00	51.89
Negative relative speed (kph)	3.99	3.60	0.00	33.52
Speed (kph)	33.55	13.79	0.00	72.90
Vehicle separation (m)	20.25	10.87	2.40	58.41

inflates test statistics used for making inferences and hypothesis testing of parameters. This paper used non-linear least squares regression with robust standard errors to estimate the parameters ignoring the effect of serial correlation. Estimating overall parameters for a group of drivers does not pose this issue and the statistical framework may be suitable to statistically evaluate the estimates.

2.2. *Estimation of driver response time lags*

The driver response time lag is defined as the time difference between the occurrence of the stimulus and the time a driver initiates a response. In this study, this time lag was estimated together with other parameters including speed, relative speed, and vehicle separation. In other words, driver response time lag was estimated simultaneously when estimating other parameters of the models. This was done by running the models in Eq. (1) for different time lags using Stata statistical software. The driver response time lag is the time lag that produces the best fitting statistical model at 5% significance level as measured by adjusted R^2.

2.3. *Estimation of driver stimulus response thresholds*

Driver response threshold is defined as the minimum difference in speed detectable by a following driver that will trigger a response. This threshold is likely to be different depending on whether the response is deceleration or acceleration. As previously discussed, a lower magnitude of the threshold was expected for deceleration response than for acceleration response. The thresholds are likely to be dependent also on the speed and vehicle separation, particularly during uncongested traffic conditions because of significant variations in speed and separation. This study calibrated the thresholds independent of these factors because during congested traffic conditions there are minimal variations in vehicle speed and separation that would cause significant differences in parameter estimates.

This paper determined stimulus thresholds using signal detection theory (SDT). The SDT theory has been used widely in situations with two or more discrete states which cannot be easily discriminated (Wickens and Hollands, 2000). For car-following situations, a driver is normally faced with three possible scenarios of the stimulus, namely, positive relative speed, zero relative speed, and negative relative speed. A driver is expected to respond by accelerating when faced with positive stimulus, to drive at a constant speed when the stimulus is too small to detect, and decelerate when faced with a negative stimulus. The combination of state of the stimulus and three possible responses is shown in Tables 3 and 4. However, since the stimulus may be too small to be detected, or for other reasons, unexpected responses may occur, therefore, field data show observations in all the six cells of Tables 3 and 4. The table shows frequency of responses of a selected driver in the dataset used in this paper for different levels of stimulus. For example, the table shows that the driver was faced with 41 situations when the relative speed was −3.2 kph. In 32 of those situations, the driver decelerated, which is expected. However, in 15 of those situations the driver remained in constant speed or accelerated, which were unexpected responses.

Fig. 2 is a plot of the data in Table 4 expressed as proportions. Based on SDT theory, the threshold value for acceleration (z_1) and for deceleration (z_2) are the points where the driver made equal numbers of expected and unexpected responses. These thresholds delimit the acceleration, no-response, and deceleration responses for the driver. For the selected driver in the dataset, the threshold for the acceleration response was 1.8 kph (1.1 mph) and for deceleration the response was −2.2 kph (1.4 mph).

3. Parameter estimates

Table 5 presents the estimated parameter estimates and shows comparative statistics between acceleration and deceleration values for three pairs of following vehicles patterns.

3.1. *Model validation approach*

The aim of validating the models is to determine whether the estimated parameters can be transferred to other sites with relatively comparable geometric and traffic characteristics.

Table 3 – State of the stimulus.

Response	Negative	Zero	Positive
Acceleration	Unexpected	Unexpected	Expected
Constant speed	Unexpected	Expected	Unexpected
Deceleration	Expected	Unexpected	Unexpected

Table 4 – Stimulus-response of an actual driver in the dataset.

Response	Stimulus (kph)									
	−4.3	−3.2	−2.2	−1.1	0	1.1	2.2	3.2	4.3	4.3
Acceleration	0	6	18	27	65	60	41	35	44	35
Constant speed	0	9	22	39	63	38	21	2	1	0
Deceleration	26	32	47	47	66	38	12	4	0	0
Total responses	26	47	87	113	192	136	74	41	45	35

The validation data used was similar to the vehicle trajectory field data but was collected on a different roadway. The data was collected from a segment of Interstate 80 in Emeryville, San Francisco, California. Similarly, this dataset was also collected as part of the FHWA's next generation simulation (NGSIM) project (NGSIM, 2008). A full detailed description of technology and methodology used to collect and process the data are available at the NGSIM website at http://ngsim.fhwa.dot.gov/.

Table 6 summarizes the validation results of statistics for corresponding car-following sub-models calibrated in this paper. Statistics for assessing validation performance of model estimates include Root Mean Square Error (RMSE) and Theil inequality coefficients (U) (Theil, 1966). The U statistic also provides additional information of its main statistic factors such as difference in mean (U_m), difference in variability(U_s), and lack of correlation(U_c). The table also contains the range of the recommended thresholds by Hourdakis et al. (2003) for calibrating and validating microscopic traffic simulation models. Overall, the results indicate that the models can be transferred to another site with relatively comparable geometric and traffic characteristics and reasonably emulate observed drivers' car-following behavior.

3.2. *Discussions of parameter estimates*

The sections discusses in detail the estimated model parameters including driver response time lags, stimulus thresholds, driver sensitivity constant, as well as speed, relative speed, and vehicle separation parameters.

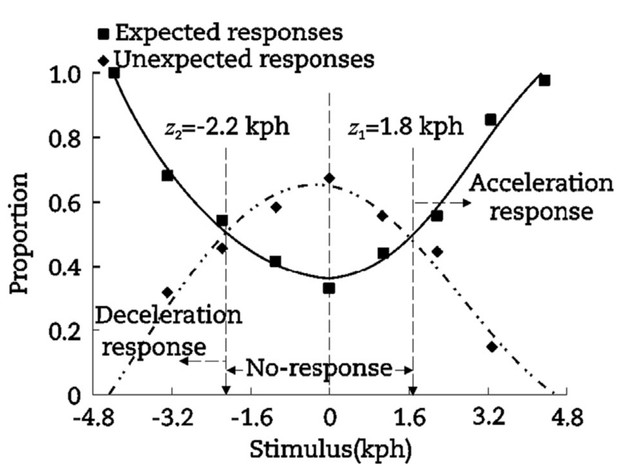

Fig. 2 – Distributions of expected and unexpected responses of an actual driver.

3.2.1. *Driver response time lags*

The results indicate that the average driver response time lags for deceleration response are lower than that for acceleration response for all movement states and vehicle types. These results are in agreement with intuitive expectation. It shows that drivers have lower response time lag when responding to a decelerating leading vehicle than when responding to an accelerating leading vehicle. This makes sense since a driver has to respond faster to a decelerating leading vehicle to avoid potential rear-end collisions. In addition, drivers' response to a decelerating vehicle may further be aided by the activation of brake lights of a leading vehicle that is braking.

The results also indicate similar driver response time lags regardless of type of vehicle being driven and/or followed. The results are intuitive due to the fact that data used were collected under congested traffic conditions where drivers usually maintain smaller separation and are more alert and cautious because of safety reasons.

3.2.2. *Stimulus response thresholds*

The results in Table 4 show that the magnitudes of the thresholds to detect negative stimulus are lower than the thresholds for detecting positive stimulus. These findings are in agreement with intuitive expectation that drivers, for safety reasons, are expected to be more aggressive when responding to a decelerating leading vehicle than an accelerating vehicle. A deceleration response is generally applied due to the need to maintain the minimum safety distance to avoid the potential rear-end collisions. On the other hand, drivers accelerate for the purpose of attaining their desired maximum speeds, which is a less critical and urgent need than deceleration response. These results are in line with those obtained by Todosiev (1963) and Michaels (1965). The threshold values, however, are lower than the ones reported by Evans and Rothery (1974) who found that under optimal driving conditions in a field, the lowest perceptible closing relative speed was 3.0 mph (4.8 kph) with a probability of 0.99 of correct detection at 197 ft (60 m) over an observation period of 4.0 s. This difference could be due to the fact that individual differences in ability to detect motion are large and dependent on vehicle speed and separation. However, for automobiles traveling behind trucks, the mean difference between acceleration response and deceleration response are insignificant. This finding can be attributed to the inability of drivers of automobiles to see vehicles immediately in front of trucks because of limited visibility. Similar to what is observed for response time lags, the mean response threshold values between different vehicle types are not statistically different.

Table 5 – Parameter estimates and comparison statistics.

Model	Acceleration response		Deceleration response		Comparison statistics		
Parameter	Mean	Std dev.	Mean	Std dev.	Mean diff.	Pooled Std dev.	*p*-value
Automobile following automobile ($n = 75$)							
Driver response time lag (s)	0.800	0.260	0.700	0.180	0.100	0.220	0.025
Stimulus threshold (kph)	2.080	1.030	1.540	0.900	0.530	0.965	0.001
Driver sensitivity β_0	1.839	3.247	−3.247	4.808	5.086	4.113	0.000
Speed β_1	−0.961	1.062	1.298	1.379	−2.259	1.234	0.000
Vehicle separation β_2	0.737	0.501	−1.544	1.216	2.281	1.018	0.000
Relative speed β_3	0.667	0.507	1.243	0.617	−0.576	0.523	0.000
Automobile following truck ($n = 25$)							
Driver response time lag (s)	0.820	0.250	0.680	0.140	0.140	0.280	0.016
Stimulus threshold (kph)	2.000	0.920	1.660	1.050	0.340	1.000	0.210*
Driver sensitivity β_0	0.906	0.242	−1.161	0.769	2.067	0.571	0.120*
Speed β_1	−1.012	1.066	1.766	1.681	−2.778	1.368	0.000
Vehicle separation β_2	0.746	0.943	−1.975	1.599	2.729	1.289	0.000
Relative speed β_3	0.778	0.613	1.226	0.914	−0.262	0.784	0.084
Truck following automobile ($n = 32$)							
Driver response time lag (s)	0.780	0.200	0.670	0.150	0.110	0.170	0.040
Stimulus threshold (kph)	2.140	1.240	1.710	0.870	0.430	1.050	0.058
Driver sensitivity β_0	1.492	1.583	−1.224	1.000	2.716	8.297	0.026
Speed β_1	−1.447	2.113	2.329	3.991	−3.776	3.205	0.000
Vehicle separation β_2	0.672	1.453	−2.352	2.895	3.024	2.294	0.000
Relative speed β_3	0.844	0.851	1.490	1.458	−0.646	1.202	0.054

Note: * indicating the difference in mean values is not statistically significant.

3.2.3. *Driver sensitivity constant, β_0*

The results in Table 5 indicate that the average driver sensitivity constant values are higher for deceleration response than for acceleration response. Similarly, the results confirm the expectation that drivers are likely to be more sensitive to deceleration response than to acceleration response because of safety concerns and activation of brake lights of the leading vehicle that is braking. The results for trucks traveling behind automobiles have a higher driver sensitivity constant for acceleration response than deceleration response, which was unexpected. This could be associated with the fact that trucks generally require a longer stopping distance and have lower acceleration capability compared to automobiles. However, there is no statistical difference in the driver sensitivity constant for automobiles traveling behind trucks. This could be due to the reasons similar to the stated above for the stimulus thresholds.

Comparison of the difference in means for different pairs of following vehicles indicated an insignificant difference in the mean values of the driver sensitivity constant. For the deceleration response, the results showed that automobiles traveling behind other automobiles have significantly higher mean values than other pairs of following vehicles under similar conditions of vehicle speed, vehicle separation, and stimulus.

3.2.4. *Speed parameter, β_1*

For the speed parameter, both the magnitude and the sign of the parameter are important. From Table 5, the sign for acceleration response is negative, whereas it is positive for deceleration. This implies that the higher the speed of the automobile the higher the magnitude of the response to deceleration and the lower its acceleration response will be. These results are logical, since one would expect that a driver already traveling at a high speed has less incentive to accelerate further but has to be more aggressive in responding to a decelerating leading vehicle for safety reasons. Another reason for this observation is that vehicles have lower acceleration capability at higher speeds.

Table 6 – Validation results and recommended thresholds.

Sub-model	Response model	Statistics for assessing validation performance				
		RMSE	U	U_m	U_s	U_c
Automobile following automobile	Acceleration	7.778	0.430	0.230	0.069	0.700
	Deceleration	9.401	0.460	0.217	0.121	0.661
Automobile following truck	Acceleration	6.048	0.378	0.057	0.055	0.887
	Deceleration	4.318	0.403	0.021	0.045	0.934
Truck following automobile	Acceleration	3.942	0.440	0.096	0.008	0.895
	Deceleration	7.928	0.434	0.155	0.193	0.651
Recommended thresholds (Hourdakis et al., 2003)		$<15\%$	<0.3	≤ 0.1	≤ 0.1	≥ 0.9

Additionally, higher magnitude of the parameter value indicates a higher magnitude of the response. The magnitudes of the parameter are also intuitive as they indicate a more aggressive (higher magnitude) response for deceleration than for acceleration.

Comparing the parameter values across vehicle types, it was observed that the magnitudes of the responses were higher for "truck following automobile." For the deceleration response, the results indicated that truck traveling behind automobiles had significantly higher mean values of the speed parameter than automobiles. This is an intuitive result because large trucks are heavier and require longer stopping and lane changing distances than automobiles. Therefore, drivers of trucks are likely to be more sensitive to speed when they are required to decelerate compared to drivers of automobiles.

3.2.5. *Vehicle separation parameter, β_2*

Both the sign and magnitude of the vehicle separation parameter are important. As shown in Table 5, the sign for acceleration response is positive while for the deceleration response is negative. A positive value indicates that the larger the vehicle separation is, the higher the magnitude of the response is and vice versa. Thus, the negative values for deceleration response indicate that the larger the vehicle separation is, the lower the magnitude of the deceleration response will be. This is intuitive since there is a lower sense of urgency to decelerate when the vehicle separation is large, while the opposite is true for smaller vehicle separation. On the other hand, the parameter for acceleration response is negative, indicating that the larger the vehicle separation is, the larger the magnitude of the acceleration response will be.

The results further indicated that the magnitude of vehicle separation parameter is higher for deceleration response than for acceleration response. As expected, the signs obtained for this parameter were intuitive, with the positive sign for the acceleration response indicating that drivers have higher magnitudes of acceleration response when vehicle separation is bigger and lower when vehicle separation is smaller. On the contrary, the negative sign for the deceleration response indicated that drivers apply higher magnitudes of deceleration response when vehicle separation is smaller and lower when vehicle separation is larger. On average, trucks traveling behind automobiles have higher magnitudes of the vehicle separation parameter value compared to automobiles.

For the acceleration response, comparisons of the differences in mean values between different vehicle types indicated insignificant differences. For the deceleration response, results showed that large trucks traveling behind automobiles have a significantly higher mean parameter value than automobiles. The results are intuitive because, generally, drivers of trucks are aware of their performance limitations compared to drivers of automobiles.

3.2.6. *Relative speed parameter, β_3*

For the relative speed parameter, both the sign and magnitude are important. A positive value indicated that the bigger the relative speed is, the higher the magnitude of the response for both acceleration and deceleration responses are and vice versa. Similarly, the results in Table 5 indicated that the mean values of the parameter for relative speed were higher for deceleration response than for acceleration response. As expected, the parameter was positive for both the acceleration and deceleration responses. This means that the bigger the magnitude of relative speed the bigger the magnitude of response, regardless of whether it was acceleration or deceleration response. In addition, the average magnitude of the parameter values for the deceleration response was higher than acceleration response. This difference in the magnitudes of the parameter confirmed that drivers are more likely to respond with higher magnitude when decelerating than when accelerating.

When comparing parameter values between different types of pairs of following vehicles, the results indicated insignificant differences in the mean values. This implies that drivers are equally sensitive to relative speed regardless of vehicle type being followed and/or driven.

4. Summary and conclusions

This paper incorporated vehicle mix in stimulus-response car-following models by estimating parameters of different pairs of following vehicles including automobile following automobile, automobile following truck, and truck following automobile. The paper used data collected on Interstate 101 in California to statistically estimate parameters of models for acceleration/deceleration to account for vehicle mix via both movement state and vehicle type. The estimated model parameters were then validated using trajectory data collected on Interstate 80 in the same region. Overall, the results demonstrated the need to use separate models depending on movement state and vehicle type being driven and/or followed. The results showed that drivers' acceleration and deceleration responses were significantly different for different pairs of following vehicles. The major findings are summarized below:

1. Driver response is different for different movement states and vehicle types. Under similar state of stimulus, drivers of automobiles respond with higher acceleration rates than drivers of trucks, whereas, drivers of trucks respond with higher deceleration rates than drivers of automobiles. It appears that drivers of trucks are more safety conscious and respond more aggressively under deceleration response.
2. Automobile drivers respond more aggressively when traveling behind automobiles than when traveling behind trucks. This could be related to the fact that trucks block visibility of drivers of automobiles traveling behind them due to their large dimensions compared to automobiles. As a result, trucks limit the ability of automobile drivers traveling behind them to see trucks beyond.
3. Model validation results indicated that the models were able to emulate the field observed drivers' behavior reasonably. Based on these results, the models demonstrated the potential to be spatially transferrable to roadways from a similar region with comparable geometric and traffic operating conditions.

The findings of this paper contribute to the understanding of drivers' car-following behavior on mixed traffic operations. This knowledge will be useful in incorporating the performance of different vehicle types for the purpose of improving the accuracy of car-following models used in traffic simulations. Ultimately, these parameter estimates would be used in traffic simulation models to improve on current performance assumptions to existing car-following equations. To that end, this will assist transportation professionals to model more accurately the impacts of existing/proposed policies and strategies to improve traffic performance on highways. The differences in parameter estimates found in this paper also highlight safety and operational concerns of mixed traffic operation on a single lane. Additionally, estimated drivers' response time lags can be used in roadway design in calculating important design parameters such as stopping sight distance on horizontal and vertical curves for different vehicle types.

The family of the models developed in this study incorporated vehicle mix in the existing stimulus-response car-following models for the observed driver car-following behavior in congested freeway traffic conditions. Due to data limitations, however, this study did not estimate a model for "truck following large truck" pattern. Drivers' behavior for such situations may be significantly different from other pairs of following vehicles calibrated in this study. Moreover, data used in this study were collected on a segment with adjacent weaving section. Drivers' behavior in vicinity of weaving section may be different from their behavior in basic freeway segments that are reasonably far from diverging and merging areas.

REFERENCES

Ahmed, K.I., 1999. Modeling Drivers' Acceleration and Lane Changing Behavior (PhD thesis). Massachusetts Institute of Technology, Cambridge.

Alvarez, L., Horowitz, R., Toy, C.V., 2003. Multi-destination traffic flow control in automated highway systems. Transportation Research Part C: Emerging Technologies 11 (1), 1–28.

Baum, C.F., 2006. An Introduction to Modern Econometric Using Stata. A Stata Press Publication, College Station, Texas.

Bonsall, P., Liu, R.H., Young, W., 2009. Modeling safety-related driving behavior-impact of parameter values. Transportation Research Part A: Policy and Practice 39 (5), 425–444.

Brackstone, M., Waterson, B., McDonald, M., 2009. Determinants of following headway in congested traffic. Transportation Research Part F: Traffic Psychology and Behaviour 12 (2), 131–142.

Dowling, R., Skabardonis, A., Halkias, J., et al., 2004. Guidelines for calibration of microsimulation models: framework and application. Transportation Research Record 1876, 1–9.

Edie, L.C., 1965. Discussion of traffic stream measurements and definitions. In: 2nd International Symposium on the Theory of Road Traffic Flow, London, 1965.

Evans, L.C., Rothery, R.W., 1974. Detection of the sign of relative motion when following a vehicle. Human Factors: The Journal of the Human Factors and Ergonomics Society 16 (2), 161–173.

Foote, R.S., 1965. Single lane traffic flow control. In: 2nd International Symposium on the Theory of Road Traffic Flow, London, 1965.

Forbes, T.W., 1963. Human factor considerations in traffic flow theory. Transportation Research Record 15, 60–66.

Gazis, D.C., Herman, R., Rothery, R.W., 1961. Nonlinear follow-the-leader models of traffic flow. Operations Research 9 (4), 545–567.

Hourdakis, J., Michalopoulos, P.G., Kottommannil, J., 2003. A practical procedure for calibrating microscopic traffic simulation models. Transportation Research Record 1852, 130–139.

Mehmood, A., Easa, S.M., 2010. Development of a new and improved driver-sensitive car-following model. Canadian Journal of Transportation 4 (1), 12–17.

Michaels, R.M., 1965. Perceptual factors in car following. In: 2nd International Symposium of Theory of Traffic Flow, Paris, 1965.

Newell, G.F., 2002. A simplified car-following theory: a lower order model. Transportation Research Part B: Methodological 36 (3), 195–205.

Next Generation Simulation (NGSIM), Next Generation Simulation (NGSIM). http://ngsim-community.org/ (accessed 20.04.08).

Ozaki, H., 1993. Reaction and anticipation in the car following behavior. In: 12th International Symposium on the Theory of Traffic Flow and Transportation, California, 1993.

Pipes, L.A., 1953. An operational analysis of traffic dynamics. Journal of Applied Physics 24 (3), 274–287.

Ranney, T.A., 1994. Models of driving behaviour: a review of their evolution. Accident Analysis and Prevention 26 (6), 733–750.

Reuschel, A., 1950. Vehicle movement in platoon. Oesterreucguschen Ingenieur_Archir 4, 193–215.

Siuhi, S., 2009. Parametric Study of Stimulus-response Behavior Incorporating Vehicle Heterogeneity in Car-following Models (PhD thesis). University of Nevada, Las Vegas.

Siuhi, S., Kaseko, M., 2013. Nonlinear acceleration and deceleration response behavior in stimulus-response car-following models. Advances in Transportation Studies 2013 (31), 81–96.

Subramanian, H., 1996. Estimation of Car-following Models (Masters thesis). Massachusetts Institute of Technology, Cambridge.

Sukthankar, R., 1997. Situation awareness in tactical driving: the role of simulation tools. Transactions Society for Computer Simulation 14 (14), 181–193.

Theil, H., 1966. Applied Economic Forecasting. North-Holland Publishing Company, Amsterdam.

Todosiev, E.P., 1963. The Action-Point Model of the Driver-vehicle-system. Report 202 A-3. The Ohio State University, Columbus.

Toledo, T., 2003. Integrating Driving Behavior Modeling (PhD thesis). Massachusetts Institute of Technology, Cambridge.

Treiber, M., Kesting, A., 2008. How much does traffic congestion increase fuel consumption and emissions? Applying a fuel consumption model to the NGSIM trajectory data. In: 87th Transportation Research Board Annual Meeting, Washington DC, 2008.

Wang, W.H., Bubb, H., Ikeuchi, K., et al., 2010a. Measurement of dangerous traffic conditions through driving dependability analysis. Journal of Scientific and Industrial Research 69 (4), 254–258.

Wang, W.H., Hou, F.G., Tan, H., et al., 2010b. A framework for function allocation in intelligent driver interface design for comfort and safety. International Journal of Computational Intelligence Systems 3 (5), 531–541.

Wang, W.H., Zhang, W., Guo, H.W., et al., 2011. A safety-based approaching behavioural model with various driving characteristics. Transportation Research Part C: Emerging Technologies 19 (6), 1202–1214.

Wang, W.H., Zhang, W., Li, D.H., et al., 2004. Improved action point model in traffic flow based on driver's cognitive mechanism. In: IEEE Intelligent Vehicles Symposium (IV04), Parma, 2004.

Wickens, C.D., Hollands, J.G., 2000. Engineering Psychology and Human Performance. Prentice-Hall Inc., New Jersey.

Winsum, W.V., Brouwer, W., 1997. Time headway in car following and operational performance during unexpected braking. Perceptual and Motor Skills 84 (3), 1247–1257.

Winsum, W.V., Heino, A., 1996. Choice of time-headway in car-following and the role of time to collision information in braking. Ergonomics 39 (4), 579–592.
Xin, W., Hourdos, J., Michalopoulos, P., et al., 2008. The less-than-perfect driver: a model of collision inclusive car-following behaviour. Transportation Research Record 2088, 126–137.
Yeo, H., 2008. Asymmetric Microscopic Driving Behavior Theory (PhD thesis). University of California, Berkeley.
Yeo, H., Skabardonis, A., 2009. Understanding stop-and-go traffic in view of asymmetric traffic theory. In: 18th International Symposium on Traffic and Transportation Theory, Hong Kong, 2009.

FURTHER READING

Abbas, M., Higgs, B., Medina, A., et al., 2010. A hybrid Wiedemann-GHR model calibration using naturalistic driving data. In: 13th International IEEE Conference on Intelligent Transportation Systems, Madeira Island, 2010.
Balachandran, K., Murugesan, K., 1994. Measuring driving performance by car-following in traffic. Ergonomics 37 (3), 427–434.
Chandler, R.E., Montroll, E.W., 1958. Traffic dynamics: studies in car following. Operations Research 6 (2), 165–184.
Colbourn, C.J., Brown, I.D., Copeman, A.K., 1978. Drivers' judgment of safe distances in vehicle following. Human Factors: The Journal of the Human Factors and Ergonomics Society 20 (1), 1–11.
Evans, L.C., Rothery, R.W., 1973. Experimental measurements of perceptual thresholds in car-following. Transportation Research Record 464, 13–29.
Gunay, B., 2008. A methodology on the automatic recognition of poor lane keeping. Journal of Advanced Transportation 42 (2), 129–150.
Ma, X.L., Andreasson, I., 2006. Estimation of driver reaction time from real following data: application in evaluation of general motor-type model. Transportation Research Record 1965, 130–141.